Read CSV Files and Import Important Libraries

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import random
import seaborn as sns
```

About Datasets

- **Netflix Prices Dataset**
- Data contains Netflix monthly subscription fees in different countries
- **Movies Titles Dataset**
- Movies and TV Shows on Netflix dataset

```
#read csv file
dfPrices = pd.read_csv("netflixPrices.csv", encoding='latin-1')
dfPrices.head()
```

```
     Country  Total Library Size  No. of TV Shows  No. of Movies  \
0  Argentina                4760             3154           1606
1    Austria                5640             3779           1861
2    Bolivia                4991             3155           1836
3   Bulgaria                6797             4819           1978
4      Chile                4994             3156           1838

   Cost Per Month - Basic ($)  Cost Per Month - Standard ($)  \
0                        3.74                           6.30
1                        9.03                          14.67
2                        7.99                          10.99
3                        9.03                          11.29
4                        7.07                           9.91

   Cost Per Month - Premium ($)
0                          9.26
1                         20.32
2                         13.99
3                         13.54
4                         12.74
```

```
#read csv file
dfTitles = pd.read_csv("moviesTitles.csv", encoding='latin-1')
dfTitles.head()
```

```
         id                               title   type  \
0  ts300399  Five Came Back: The Reference Films   SHOW
```

```
1   tm84618                          Taxi Driver  MOVIE
2  tm154986                          Deliverance  MOVIE
3  tm127384      Monty Python and the Holy Grail  MOVIE
4  tm120801                      The Dirty Dozen  MOVIE

                                         description  release_year  \
0  This collection includes 12 World War II-era p...          1945
1  A mentally unstable Vietnam War veteran works ...          1976
2  Intent on seeing the Cahulawassee River before...          1972
3  King Arthur, accompanied by his squire, recrui...          1975
4  12 American military prisoners in World War II...          1967

  age_certification  runtime
genres  \
0             TV-MA       51
['documentation']
1                 R      114                          ['drama',
'crime']
2                 R      109  ['drama', 'action', 'thriller',
'european']
3                PG       91              ['fantasy', 'action',
'comedy']
4               NaN      150                            ['war',
'action']

  production_countries  seasons    imdb_id  imdb_score  imdb_votes  \
0               ['US']      1.0        NaN         NaN         NaN
1               ['US']      NaN  tt0075314         8.2    808582.0
2               ['US']      NaN  tt0068473         7.7    107673.0
3               ['GB']      NaN  tt0071853         8.2    534486.0
4         ['GB', 'US']      NaN  tt0061578         7.7     72662.0

   tmdb_popularity  tmdb_score
0            0.600         NaN
1           40.965       8.179
2           10.010       7.300
3           15.461       7.811
4           20.398       7.600
```

1. Data Preprocessing

1.1 Data Cleaning

1.1.1 Checking For Missing and Duplicate Values

Netflix Prices Dataframe

```
# checking for null values
dfPrices.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 65 entries, 0 to 64
Data columns (total 7 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   Country                       65 non-null     object 
 1   Total Library Size            65 non-null     int64  
 2   No. of TV Shows               65 non-null     int64  
 3   No. of Movies                 65 non-null     int64  
 4   Cost Per Month - Basic ($)    65 non-null     float64
 5   Cost Per Month - Standard ($) 65 non-null     float64
 6   Cost Per Month - Premium ($)  65 non-null     float64
dtypes: float64(3), int64(3), object(1)
memory usage: 3.7+ KB
```

```
# checking for duplicates
True in dfPrices.duplicated().values
```

```
False
```

From the information above, we can see that either Missing values or Duplicate in the Netflix Prices Dataset does not exist.

Movies Titles Dataframe

For the Movies Titles Data Frame there are some features or columns that are not needed in our data analysis processes. So we could drop these features and only keep the features that are important.

```
dfTitles = dfTitles.drop(['id', 'title', 'description', 'imdb_id', 
'age_certification', 'seasons'], axis=1)
```

```
dfTitles.head()
```

```
    type  release_year  runtime                                   
genres  \
0   SHOW          1945       51                                   
['documentation']   
1  MOVIE          1976      114                         ['drama', 
'crime']   
2  MOVIE          1972      109  ['drama', 'action', 'thriller', 
'european']   
3  MOVIE          1975       91             ['fantasy', 'action', 
'comedy']   
4  MOVIE          1967      150                           ['war', 
'action']   

  production_countries  imdb_score  imdb_votes  tmdb_popularity  
tmdb_score  
0               ['US']         NaN         NaN            0.600  
NaN  
```

```
1              ['US']        8.2    808582.0           40.965
8.179
2              ['US']        7.7    107673.0           10.010
7.300
3              ['GB']        8.2    534486.0           15.461
7.811
4        ['GB', 'US']        7.7     72662.0           20.398
7.600
```

```
# checking for null values
dfTitles.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5850 entries, 0 to 5849
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   type                  5850 non-null   object
 1   release_year          5850 non-null   int64
 2   runtime               5850 non-null   int64
 3   genres                5850 non-null   object
 4   production_countries  5850 non-null   object
 5   imdb_score            5368 non-null   float64
 6   imdb_votes            5352 non-null   float64
 7   tmdb_popularity       5759 non-null   float64
 8   tmdb_score            5539 non-null   float64
dtypes: float64(4), int64(2), object(3)
memory usage: 411.5+ KB
```

From the above information, we can see that we have 5 columns (imdb_score, imdb_votes, tmdb_popularity, tmdb_score) that have missing values.

These columns are quantitative data thus we can solve this problem by filling these missing values with their mean values.

```
# fill in NaN with mean values
dfTitles['imdb_score'] =
dfTitles['imdb_score'].fillna(dfTitles['imdb_score'].mean())
dfTitles['tmdb_score'] =
dfTitles['tmdb_score'].fillna(dfTitles['tmdb_score'].mean())
dfTitles['imdb_votes'] =
dfTitles['imdb_votes'].fillna(dfTitles['imdb_votes'].mean())
dfTitles['imdb_votes'] = dfTitles['imdb_votes'].astype(np.int64)
dfTitles['tmdb_popularity'] =
dfTitles['tmdb_popularity'].fillna(dfTitles['tmdb_popularity'].mean())

dfTitles.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5850 entries, 0 to 5849
Data columns (total 9 columns):
```

```
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   type                  5850 non-null   object 
 1   release_year          5850 non-null   int64  
 2   runtime               5850 non-null   int64  
 3   genres                5850 non-null   object 
 4   production_countries  5850 non-null   object 
 5   imdb_score            5850 non-null   float64
 6   imdb_votes            5850 non-null   int64  
 7   tmdb_popularity       5850 non-null   float64
 8   tmdb_score            5850 non-null   float64
dtypes: float64(3), int64(3), object(3)
memory usage: 411.5+ KB
```

2. Sampling

2.1 Stratified Random Sampling for the Netflix Prices dataframe population

```
# Stratified sampling
Dependent = dfPrices['Cost Per Month - Basic ($)']

# to get the most and least basic price
print(Dependent.sort_values(ascending=True).head(1))
print(Dependent.sort_values(ascending=False).head(1))
```

```
41    1.97
Name: Cost Per Month - Basic ($), dtype: float64
61    12.88
Name: Cost Per Month - Basic ($), dtype: float64
```

```
# make a new column with the strata of the entry
dfPrices['s'] = 0


for i in range(len(dfPrices)):
    if Dependent[i] > 1.5 and Dependent[i] <= 3.8:
        dfPrices['s'][i] = 1
    elif Dependent[i] > 3.8 and Dependent[i] <= 6.1:
        dfPrices['s'][i] = 2
    elif Dependent[i] > 6.1 and Dependent[i] <= 8.4:
        dfPrices['s'][i] = 3
    elif Dependent[i] > 8.4 and Dependent[i] <= 10.7:
        dfPrices['s'][i] = 4
    elif Dependent[i] > 10.7 and Dependent[i] <= 13:
        dfPrices['s'][i] = 5

dfPrices.head()
```

```
     Country  Total Library Size  No. of TV Shows  No. of Movies  \
0  Argentina                4760             3154           1606   
1    Austria                5640             3779           1861   
2    Bolivia                4991             3155           1836   
```

```
3   Bulgaria                6797             4819           1978
4      Chile                4994             3156           1838

   Cost Per Month - Basic ($)  Cost Per Month - Standard ($)  \
0                        3.74                           6.30
1                        9.03                          14.67
2                        7.99                          10.99
3                        9.03                          11.29
4                        7.07                           9.91

   Cost Per Month - Premium ($)  s
0                          9.26  1
1                         20.32  4
2                         13.99  3
3                         13.54  4
4                         12.74  3
```

```
strata = dfPrices['s']
strata.value_counts()
```

```
4    33
3    22
5     4
1     3
2     3
Name: s, dtype: int64
```

```
# make percentages list to use in sampling
percentages = list(dfPrices['s'].value_counts() / len(dfPrices))
percentages
```

```
[0.5076923076923077,
 0.3384615384615385,
 0.06153846153846154,
 0.046153846153846156,
 0.046153846153846156]
```

```
sampleSize = 20

s1 = strata[strata ==
strata.value_counts().index[0]].sample(round(sampleSize
*percentages[0]))
s2 = strata[strata ==
strata.value_counts().index[1]].sample(round(sampleSize
*percentages[1]))
s3 = strata[strata ==
strata.value_counts().index[2]].sample(round(sampleSize
*percentages[2]))
s4 = strata[strata ==
strata.value_counts().index[3]].sample(round(sampleSize
*percentages[3]))
```

```python
s5 = strata[strata ==
strata.value_counts().index[4]].sample(round(sampleSize
*percentages[4]))

s = s1.append([s2,s3,s4,s5])

# make the sample dataframe from the required indices
indices = s.index.values

dfPricesSample = pd.DataFrame()

dfPricesSample = dfPrices.loc[indices, :]

dfPricesSample
```

```
        Country  Total Library Size  No. of TV Shows  No. of Movies  \
7       Croatia                2274             1675            599
52  Netherlands                5376             3779           1597
47      Finland                4045             2638           1407
26      Moldova                3937             2473           1464
3      Bulgaria                6797             4819           1978
13    Gibraltar                6167             4079           2088
55    Lithuania                6462             4490           1972
1       Austria                5640             3779           1861
21        Italy                5183             3545           1638
12      Germany                5668             3814           1854
58    Indonesia                3887             2449           1438
24     Malaysia                5952             3565           2387
17    Hong Kong                4746             2883           1863
62    Australia                6114             4050           2064
16     Honduras                4989             3154           1835
15    Guatemala                4767             3154           1613
4         Chile                4994             3156           1838
53       Sweden                4361             2973           1388
41       Turkey                4639             2930           1709
42      Ukraine                5336             3261           2075

    Cost Per Month - Basic ($)  Cost Per Month - Standard ($)  \
7                         9.03                          11.29
52                        9.03                          13.54
47                        9.03                          13.54
26                        9.03                          11.29
3                         9.03                          11.29
13                        9.03                          14.67
55                        9.03                          11.29
1                         9.03                          14.67
21                        9.03                          14.67
12                        9.03                          14.67
58                        8.36                          10.66
24                        8.29                          10.65
```

```
17                          8.08                          10.00
62                          7.84                          12.12
16                          7.99                          10.99
15                          7.99                          10.99
4                           7.07                           9.91
53                         10.90                          14.20
41                          1.97                           3.00
42                          5.64                           8.46

    Cost Per Month - Premium ($)  s
7                          13.54  4
52                         18.06  4
47                         18.06  4
26                         13.54  4
3                          13.54  4
13                         20.32  4
55                         13.54  4
1                          20.32  4
21                         20.32  4
12                         20.32  4
58                         12.96  3
24                         13.02  3
17                         11.93  3
62                         16.39  3
16                         13.99  3
15                         13.99  3
4                          12.74  3
53                         19.70  5
41                          4.02  1
42                         11.29  2
```

2.2 Cluster Sampling on the Movies Titles Data Frame

```
dfTitles.index.values
```

```
array([   0,    1,    2, ..., 5847, 5848, 5849])
```

```
from sklearn.cluster import KMeans

int_cols = dfTitles.loc[:,dfTitles.dtypes=='int64']
float_cols = dfTitles.loc[:,dfTitles.dtypes=='float64']

X = pd.merge(left=int_cols,right= float_cols,on=dfTitles.index.values)

kmeans = KMeans(n_clusters=5).fit(X)
dfTitles['cluster'] = kmeans.labels_

dfTitles.cluster.value_counts()
```

```
0    5469
3     286
```

```
1      77
2      12
4       6
Name: cluster, dtype: int64
```

```
dfTitlesSample = dfTitles[dfTitles.cluster.isin([1, 2, 4])]
dfTitlesSample
```

```
       type  release_year  runtime
genres  \
1     MOVIE          1976      114                          ['drama',
'crime']
3     MOVIE          1975       91             ['fantasy', 'action',
'comedy']
6     MOVIE          1979       94
['comedy']
35     SHOW          1989       24
['comedy']
36    MOVIE          1990      145                          ['drama',
'crime']
...     ...           ...      ...
...
3061   SHOW          2020       56                          ['drama',
'sport']
3076  MOVIE          2019      209  ['crime', 'drama', 'history',
'thriller']
3095  MOVIE          2019      136              ['drama', 'romance',
'comedy']
4719   SHOW          2021       55             ['action', 'thriller',
'drama']
4726  MOVIE          2021      138                ['comedy', 'drama',
'scifi']

     production_countries  imdb_score  imdb_votes  tmdb_popularity  \
1                   ['US']        8.2      808582           40.965
3                   ['GB']        8.2      534486           15.461
6                   ['GB']        8.0      395024           17.770
35                  ['US']        8.9      308824          130.213
36                  ['US']        8.7     1131681           50.387
...                    ...        ...         ...              ...
3061                ['US']        8.6      420100           82.702
3076                ['US']        7.8      376379           21.075
3095                ['GB']        7.9      298303           28.268
4719                ['KR']        8.0      426967          361.925
4726                ['US']        7.2      515337          120.874

      tmdb_score  cluster
1          8.179        2
3          7.811        1
6          7.800        1
```

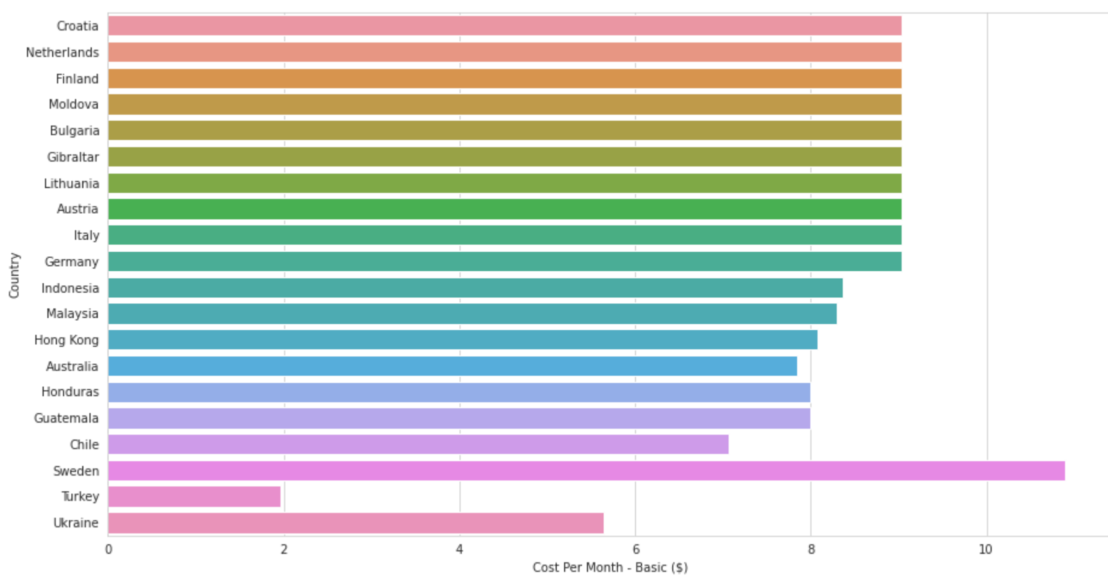
```
35          8.301       1
36          8.463       2
...           ...     ...
3061        8.624       1
3076        7.600       1
3095        7.800       1
4719        7.821       1
4726        7.208       1

[95 rows x 10 columns]
```

3. EDA (Explaratory Data Analysis)

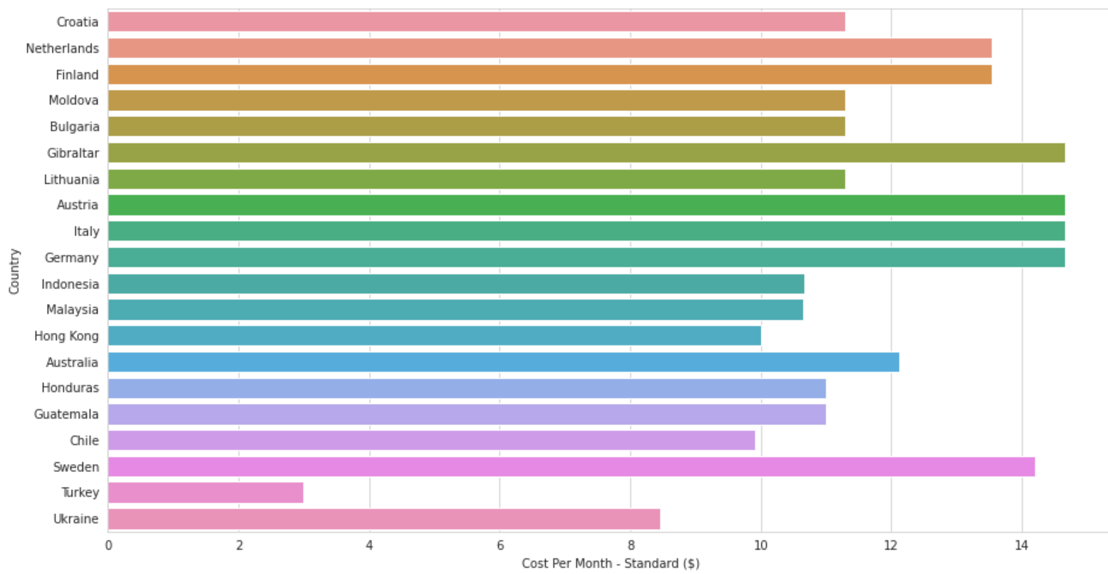
The Explaratory Data Analysis step will help us analyze the data to find interesting facts.

Univariate Visulaizations on the Netflix Prices Data Frame

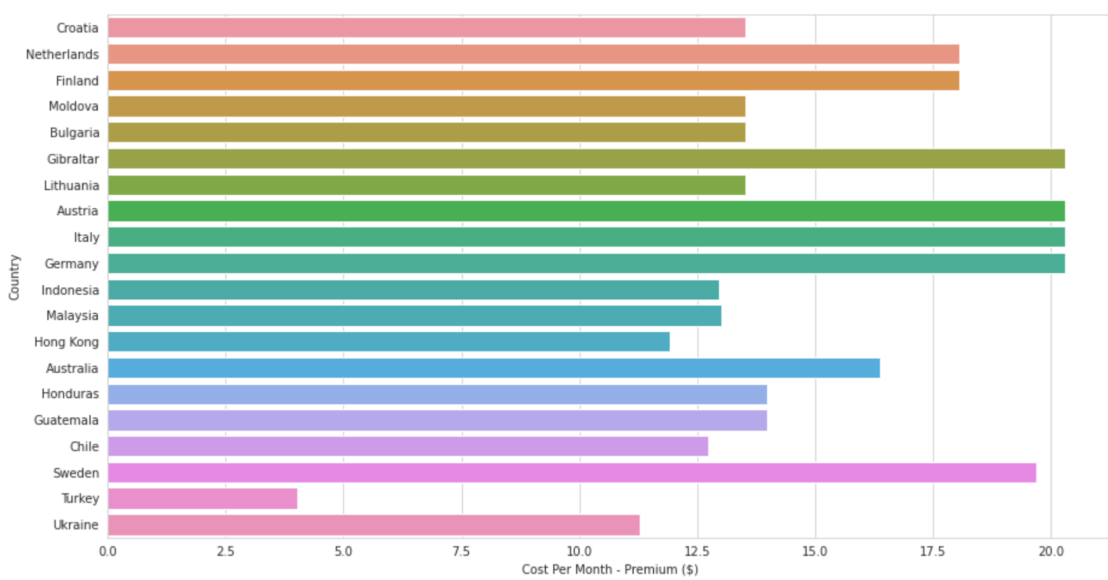
```
sns.set_style("whitegrid")
plt.figure(figsize=(15,8))
sns.barplot(y='Country', x='Cost Per Month - Basic ($)',
data=dfPricesSample);
```




```
sns.set_style("whitegrid")
plt.figure(figsize=(15,8))
sns.barplot(y='Country', x='Cost Per Month - Standard ($)',
data=dfPricesSample);
```




```
sns.set_style("whitegrid")
plt.figure(figsize=(15,8))
sns.barplot(y='Country', x='Cost Per Month - Premium ($)',
data=dfPricesSample);
```

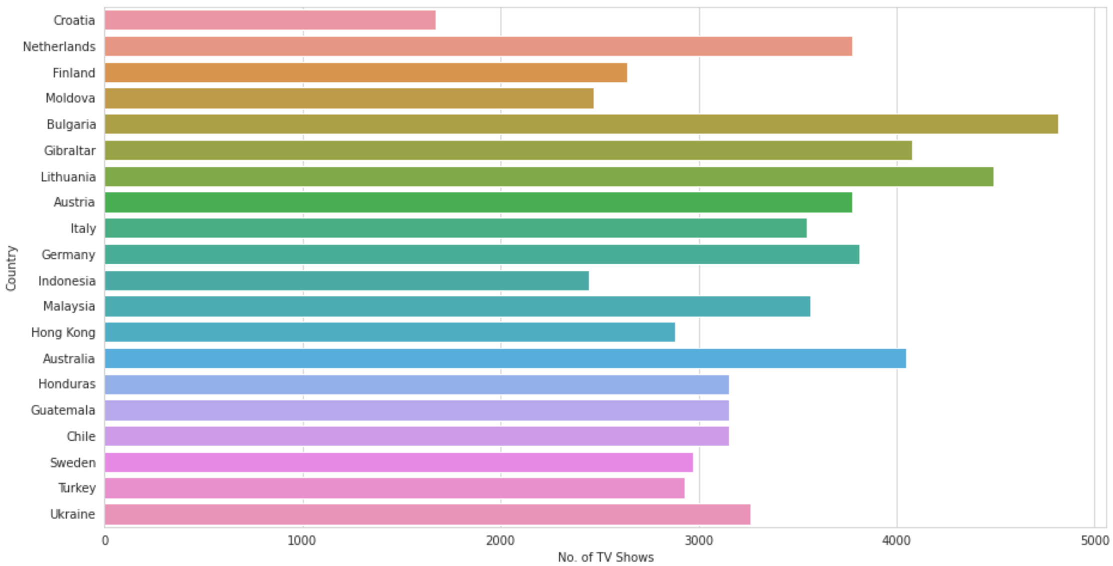



```
dfPricesSample.head()
```

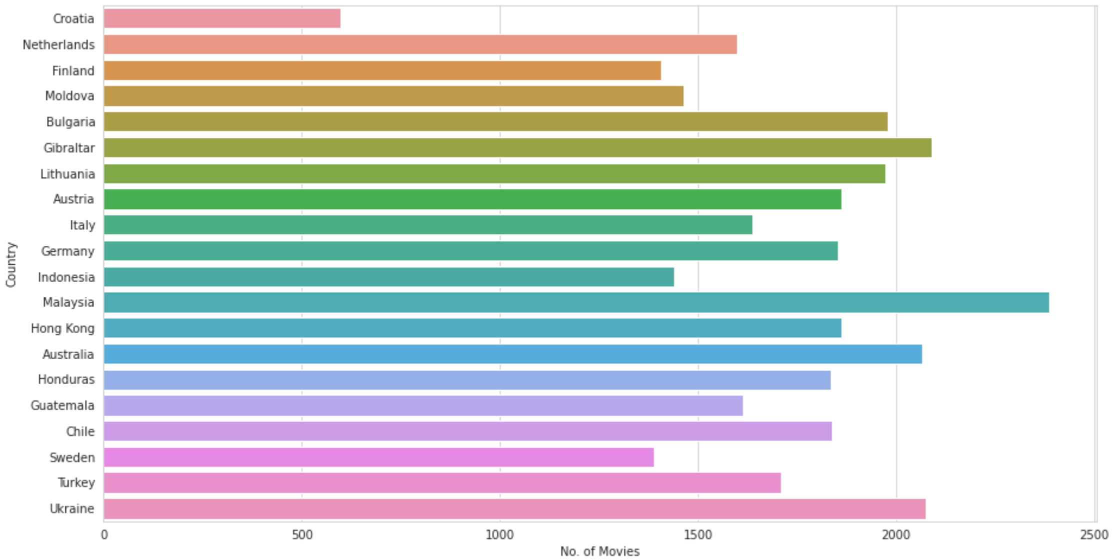
```
        Country  Total Library Size  No. of TV Shows  No. of Movies  \
7       Croatia                2274             1675            599
52  Netherlands                5376             3779           1597
47      Finland                4045             2638           1407
26      Moldova                3937             2473           1464
3      Bulgaria                6797             4819           1978

    Cost Per Month - Basic ($)  Cost Per Month - Standard ($)  \
```

```
7                          9.03                          11.29
52                         9.03                          13.54
47                         9.03                          13.54
26                         9.03                          11.29
3                          9.03                          11.29

    Cost Per Month - Premium ($)  s
7                          13.54  4
52                         18.06  4
47                         18.06  4
26                         13.54  4
3                          13.54  4
```

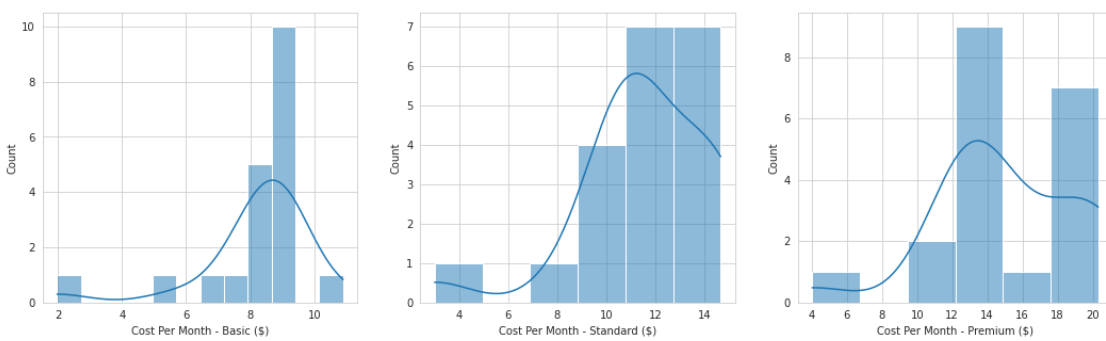
```
sns.set_style("whitegrid")
plt.figure(figsize=(15,8))
sns.barplot(y='Country', x='No. of TV Shows', data=dfPricesSample);
```




```
sns.set_style("whitegrid")
plt.figure(figsize=(15,8))
sns.barplot(y='Country', x='No. of Movies', data=dfPricesSample);
```




```
# countries with the same cost
plt.figure(figsize = [18, 5])
plt.subplot(1, 3, 1)
sns.histplot(dfPricesSample['Cost Per Month - Basic ($)'], kde=True);
plt.subplot(1, 3, 2)
sns.histplot(dfPricesSample['Cost Per Month - Standard ($)'],
kde=True);
plt.subplot(1, 3, 3)
sns.histplot(dfPricesSample['Cost Per Month - Premium ($)'],
kde=True);
```




```
# different subscriptions prices' mean that we found above
print(dfPricesSample['Cost Per Month - Basic ($)'].mean())
print(dfPricesSample['Cost Per Month - Standard ($)'].mean())
print(dfPricesSample['Cost Per Month - Premium ($)'].mean())
```

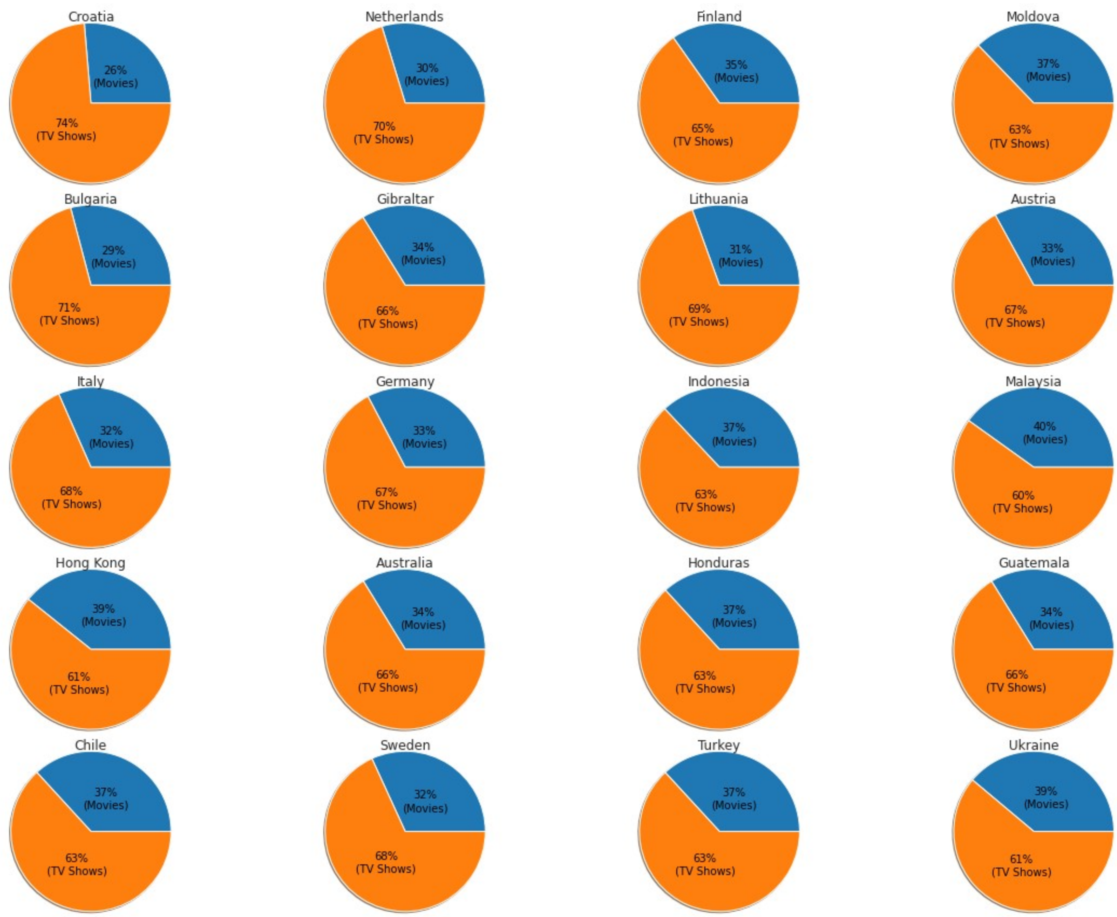
```
8.221499999999999
11.594999999999999
15.0795
```

```
======================================================================
==========
```

Here we found that netflix industry in all sample countries relies on TV Shows the most

```
dfPrices.head()

     Country  Total Library Size  No. of TV Shows  No. of Movies  \
0  Argentina                4760             3154           1606
1    Austria                5640             3779           1861
2    Bolivia                4991             3155           1836
3   Bulgaria                6797             4819           1978
4      Chile                4994             3156           1838

   Cost Per Month - Basic ($)  Cost Per Month - Standard ($)  \
0                        3.74                           6.30
1                        9.03                          14.67
2                        7.99                          10.99
3                        9.03                          11.29
4                        7.07                           9.91

   Cost Per Month - Premium ($)  s
0                          9.26  1
1                         20.32  4
2                         13.99  3
3                         13.54  4
4                         12.74  3

dfPricesSample.head()

        Country  Total Library Size  No. of TV Shows  No. of Movies  \
7       Croatia                2274             1675            599
52  Netherlands                5376             3779           1597
47      Finland                4045             2638           1407
26      Moldova                3937             2473           1464
3      Bulgaria                6797             4819           1978

    Cost Per Month - Basic ($)  Cost Per Month - Standard ($)  \
7                         9.03                          11.29
52                        9.03                          13.54
47                        9.03                          13.54
26                        9.03                          11.29
3                         9.03                          11.29

    Cost Per Month - Premium ($)  s
7                          13.54  4
52                         18.06  4
47                         18.06  4
26                         13.54  4
3                          13.54  4

dfPrices_Library = dfPricesSample[['Country', 'Total Library Size',
'No. of Movies', 'No. of TV Shows']]
```

```
countryList = list(dfPrices_Library['Country'])
numMoviesList = list(dfPrices_Library['No. of Movies'])
numTvShowsList = list(dfPrices_Library['No. of TV Shows'])

pieLabels = ["Movies", "TV Shows"]

labelChoice = -1

def labelsMaker(p):
    global labelChoice
    labelChoice += 1
    return "{:0.0f}%\n({:s})".format(p, pieLabels[labelChoice%2])

plt.figure(figsize = [20, 15])
for i in range(len(dfPricesSample)):
    sub = plt.subplot(5, 4, i+1)
    sub.set_title(countryList[i])
    pieData = np.array([numMoviesList[i], numTvShowsList[i]])
    plt.pie(pieData, pctdistance=0.45, autopct=lambda p :
labelsMaker(p), radius=1.32, textprops={'color':"black"}, shadow=True)
```

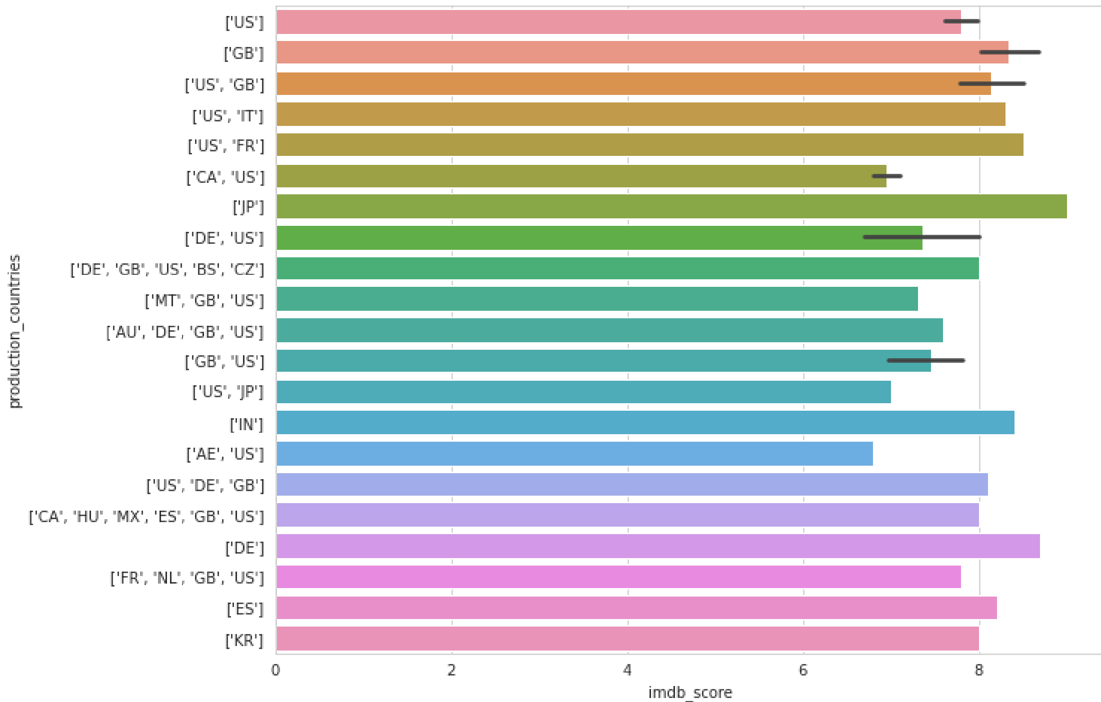


Univariate Visulaizations on the Movies Titles Data Frame

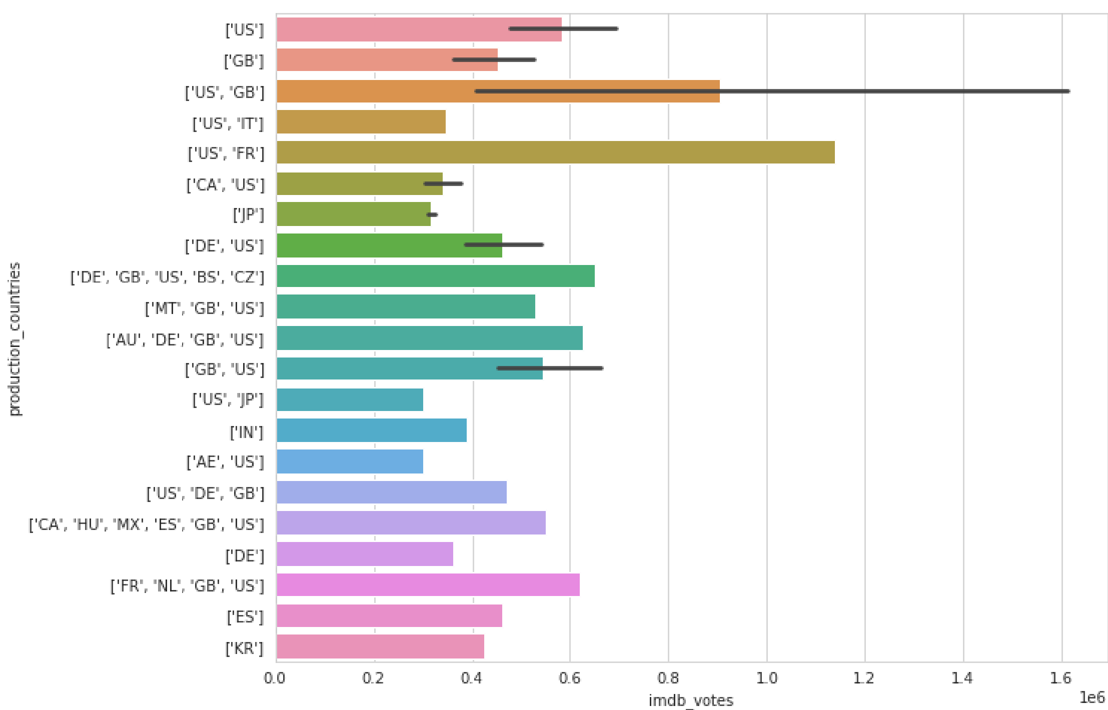
```
dfTitlesSample.head()
```

```
     type  release_year  runtime                               genres  \
1   MOVIE          1976      114                  ['drama', 'crime']
3   MOVIE          1975       91  ['fantasy', 'action', 'comedy']
6   MOVIE          1979       94                          ['comedy']
35   SHOW          1989       24                          ['comedy']
36  MOVIE          1990      145                  ['drama', 'crime']

   production_countries  imdb_score  imdb_votes  tmdb_popularity
tmdb_score  \
1                ['US']         8.2      808582           40.965
8.179
3                ['GB']         8.2      534486           15.461
7.811
6                ['GB']         8.0      395024           17.770
7.800
35               ['US']         8.9      308824          130.213
8.301
36               ['US']         8.7     1131681           50.387
8.463

    cluster
1         2
3         1
6         1
35        1
36        2
```

```
sns.set_style("whitegrid")
plt.figure(figsize=(10,8))
sns.barplot(y='production_countries', x='imdb_score',
data=dfTitlesSample);
```

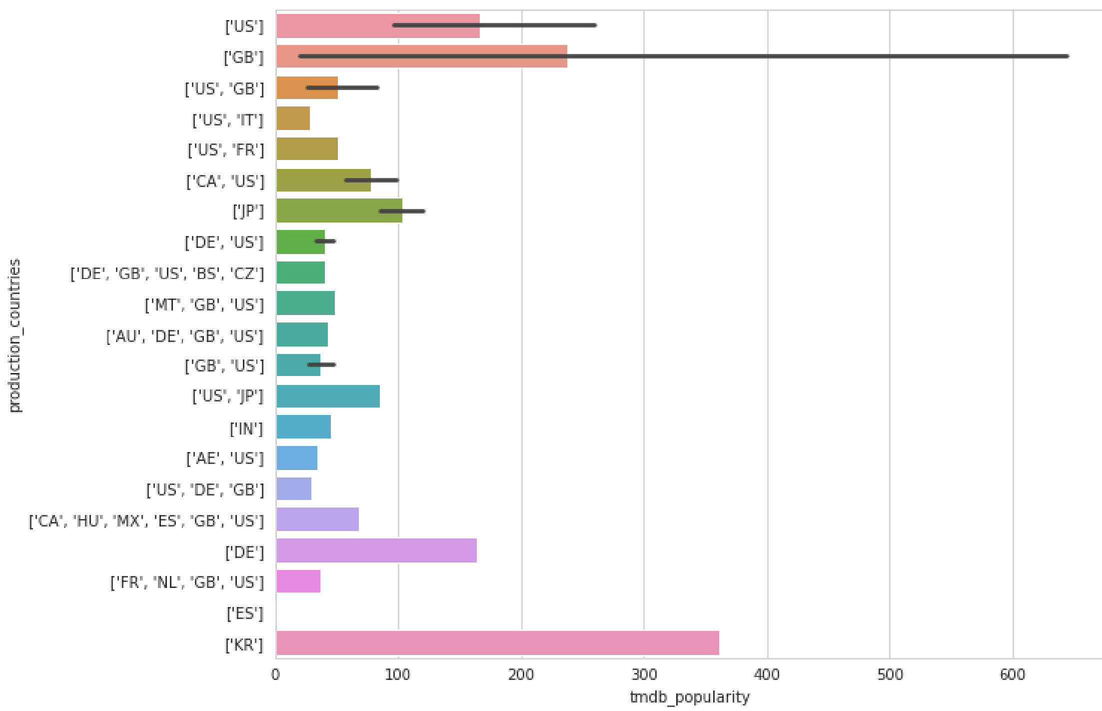



```
sns.set_style("whitegrid")
plt.figure(figsize=(10,8))
sns.barplot(y='production_countries', x='imdb_votes',
data=dfTitlesSample);
```

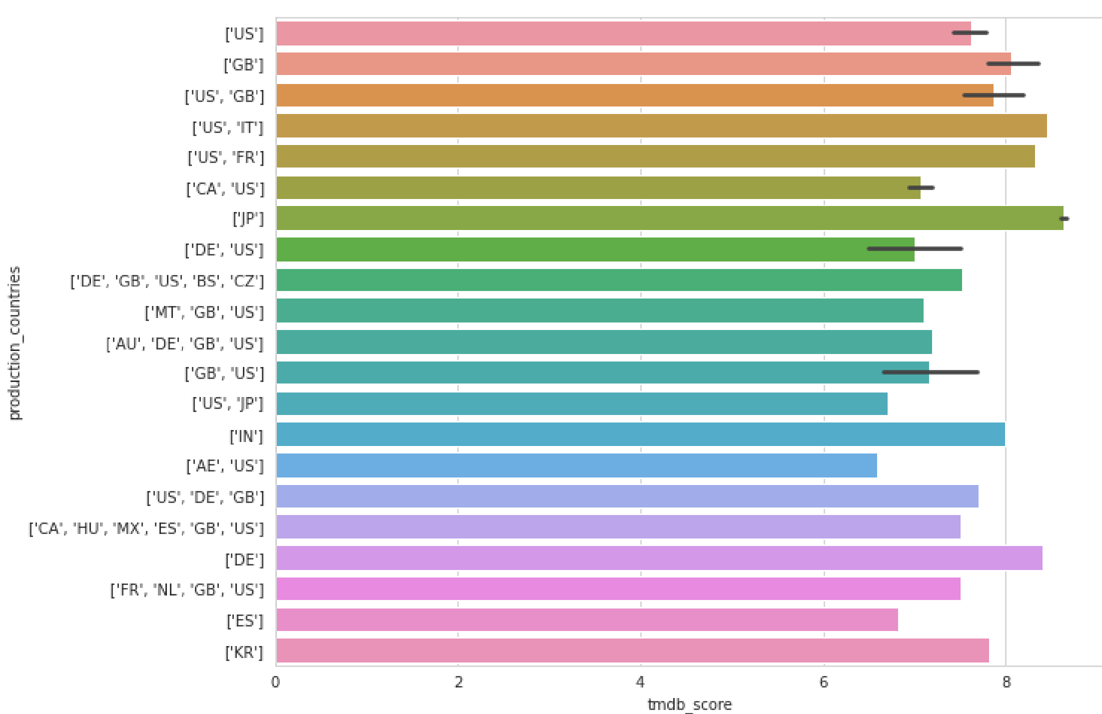



```
sns.set_style("whitegrid")
plt.figure(figsize=(10,8))
```

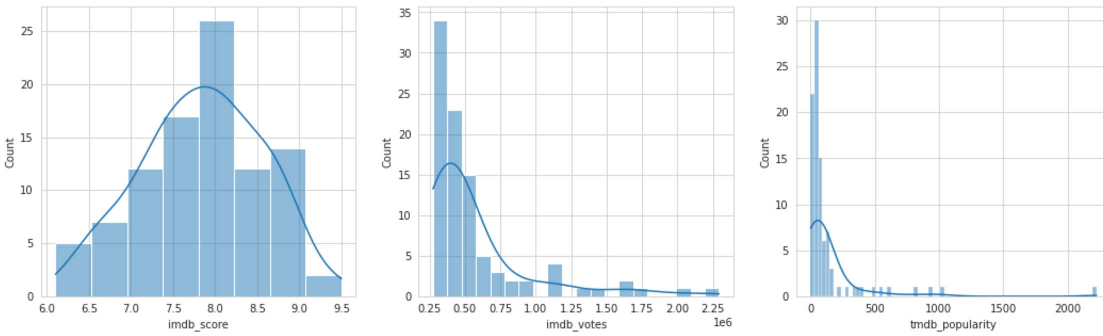
```
sns.barplot(y='production_countries', x='tmdb_popularity',
data=dfTitlesSample);
```




```
sns.set_style("whitegrid")
plt.figure(figsize=(10,8))
sns.barplot(y='production_countries', x='tmdb_score',
data=dfTitlesSample);
```



```
plt.figure(figsize = [18, 5])
plt.subplot(1, 3, 1)
sns.histplot(dfTitlesSample['imdb_score'], kde=True);
plt.subplot(1, 3, 2)
sns.histplot(dfTitlesSample['imdb_votes'], kde=True);
plt.subplot(1, 3, 3)
sns.histplot(dfTitlesSample['tmdb_popularity'], kde=True);
```

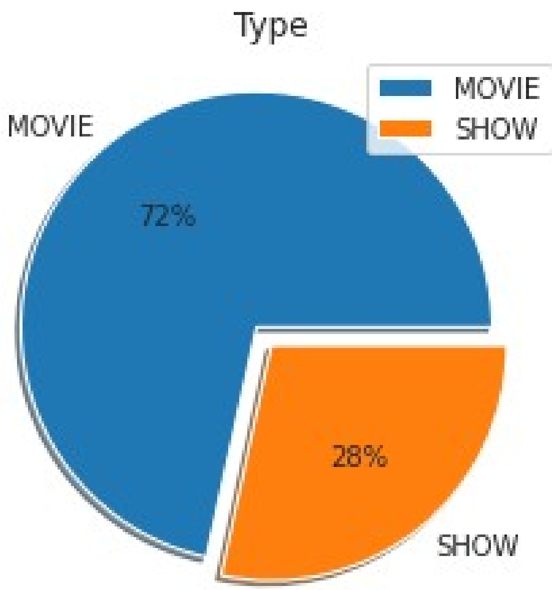



```
print(dfTitlesSample['imdb_score'].mean())
print(dfTitlesSample['imdb_votes'].mean())
print(dfTitlesSample['tmdb_popularity'].mean())
```

```
7.837894736842104
566966.9263157895
137.77025263157896
```

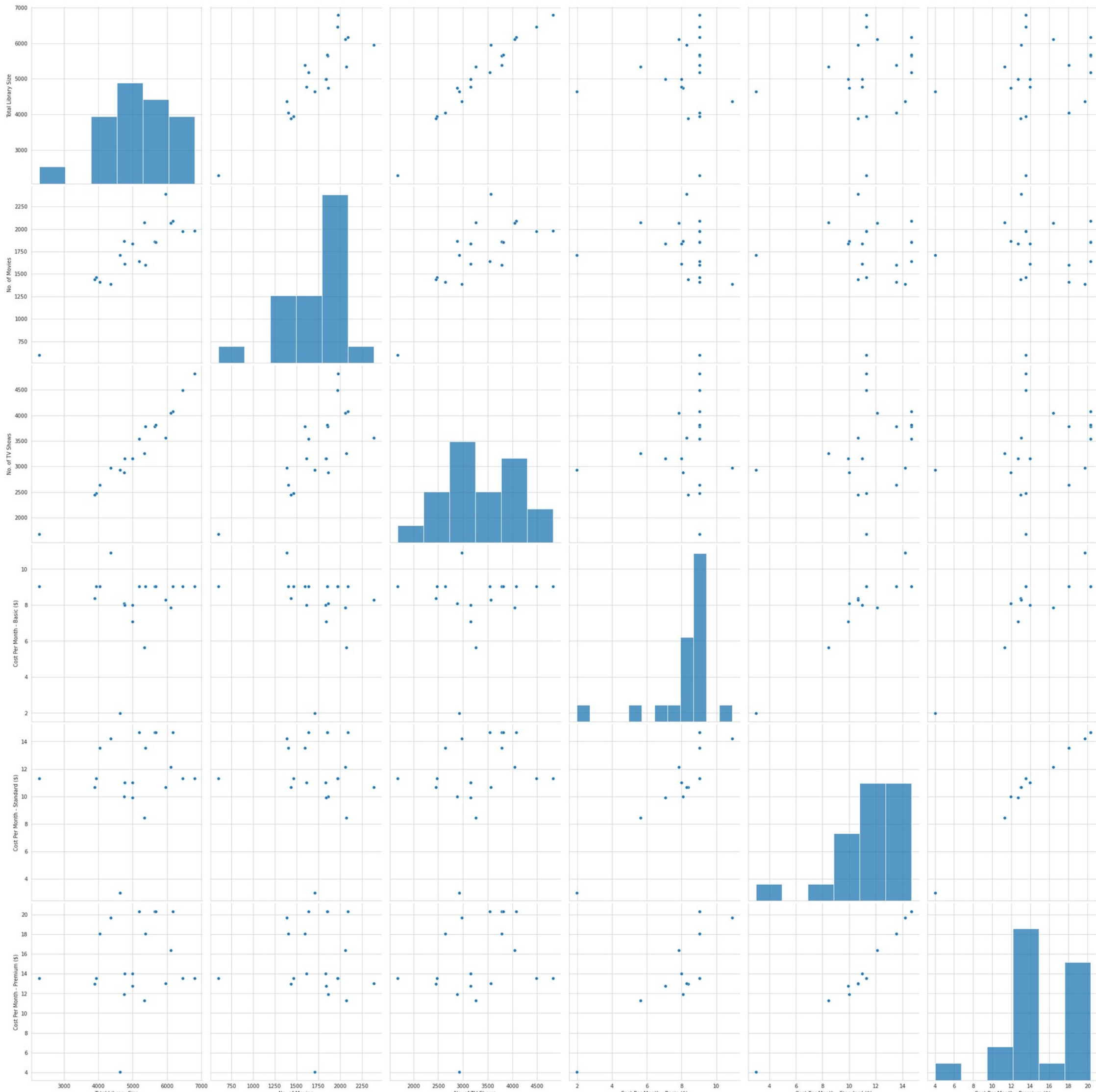
```
# pie chart
plt.pie(dfTitlesSample['type'].value_counts(normalize=True), labels =
dfTitlesSample['type'].value_counts(normalize=True).index,
autopct='%1.0f%%', shadow=True, explode=[0.1, 0], radius=1)
plt.legend()
plt.title("Type")
```

```
Text(0.5, 1.0, 'Type')
```



Bivariate Visualizations on Netflix Prices Data Frame

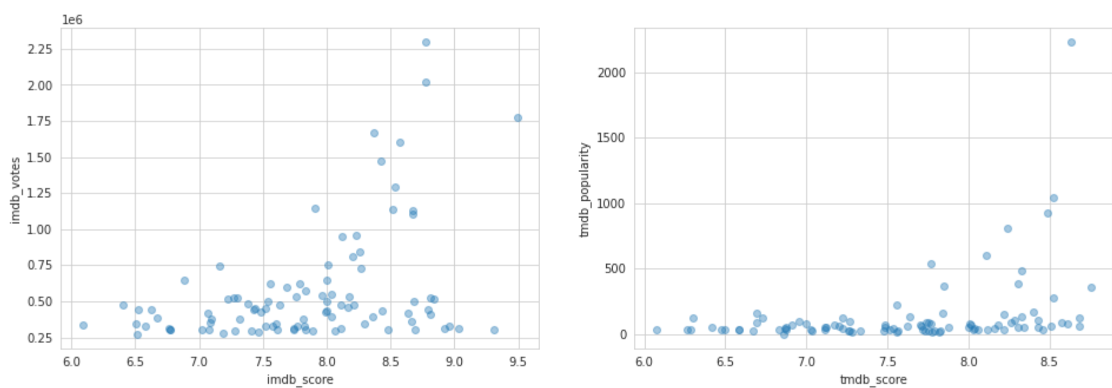
```
dfPricesTest = dfPricesSample[['Total Library Size', 'No. of Movies',
'No. of TV Shows', 'Cost Per Month - Basic ($)', 'Cost Per Month -
Standard ($)', 'Cost Per Month - Premium ($)']]
sns.pairplot(data = dfPricesTest, height = 5);
```



```
dfPrices_corr = dfPrices[['Total Library Size', 'No. of TV Shows',
'No. of Movies', 'Cost Per Month - Basic ($)', 'Cost Per Month -
Standard ($)', 'Cost Per Month - Premium ($)']].corr()
dfPrices_corr

plt.figure(figsize=(14,5))
sns.heatmap(dfPrices_corr, annot=True);
```

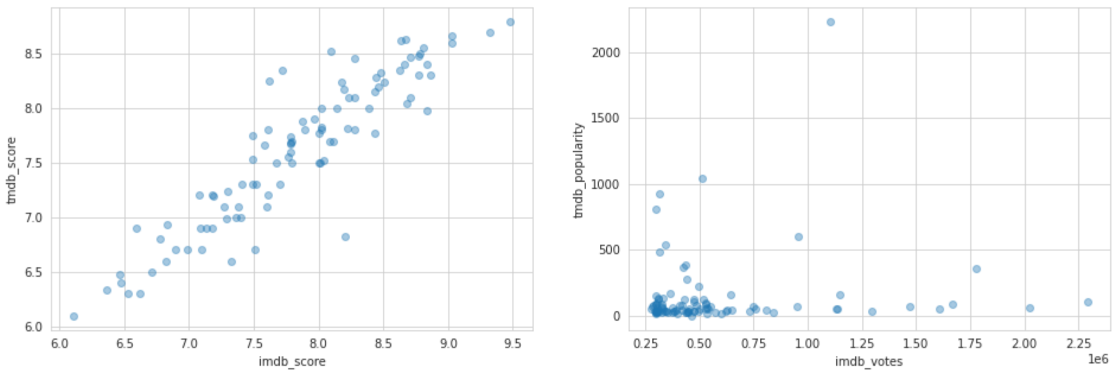
Bivariate Visualizations on Movies Titles Data Frame

```
# scatterplot to show the relation between carat and prices
plt.figure(figsize = [16, 5])

plt.subplot(1, 2, 1)
sns.regplot(data = dfTitlesSample, x = 'imdb_score', y = 'imdb_votes',
x_jitter=0.04, scatter_kws={'alpha':0.4}, fit_reg=False)
plt.xlabel('imdb_score');
plt.ylabel('imdb_votes');
plt.subplot(1, 2, 2)
sns.regplot(data = dfTitlesSample, x = 'tmdb_score', y =
'tmdb_popularity', x_jitter=0.04, scatter_kws={'alpha':0.4},
fit_reg=False)
plt.xlabel('tmdb_score');
plt.ylabel('tmdb_popularity');
```

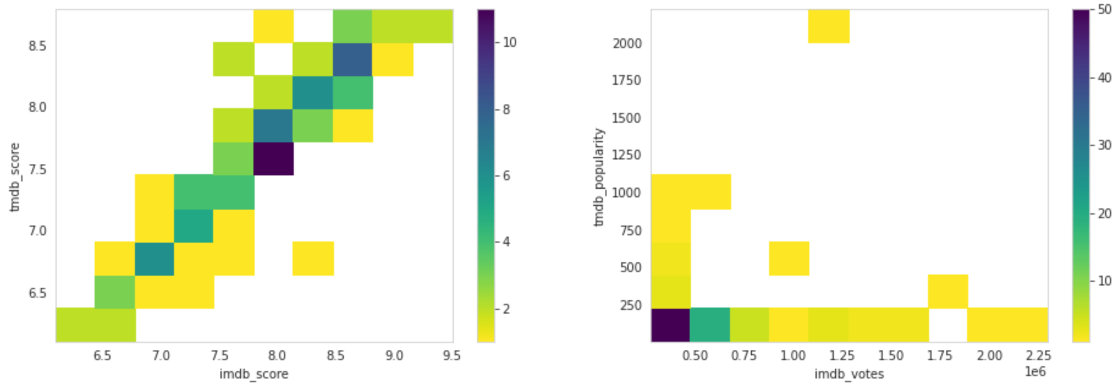



```
# scatterplot to show the relation between carat and prices
plt.figure(figsize = [16, 5])

plt.subplot(1, 2, 1)
```

```
sns.regplot(data = dfTitlesSample, x = 'imdb_score', y = 'tmdb_score',
x_jitter=0.04, scatter_kws={'alpha':0.4}, fit_reg=False)
plt.xlabel('imdb_score');
plt.ylabel('tmdb_score');
plt.subplot(1, 2, 2)
sns.regplot(data = dfTitlesSample, x = 'imdb_votes', y =
'tmdb_popularity', x_jitter=0.04, scatter_kws={'alpha':0.4},
fit_reg=False)
plt.xlabel('imdb_votes');
plt.ylabel('tmdb_popularity');
```




```
# heatmap between table and depth
plt.figure(figsize = [16, 5])

plt.subplot(1, 2, 1)
plt.hist2d(data = dfTitlesSample, x = 'imdb_score', y = 'tmdb_score',
cmin=0.5, cmap='viridis_r')
plt.colorbar()
plt.xlabel('imdb_score')
plt.ylabel('tmdb_score');

plt.subplot(1, 2, 2)
plt.hist2d(data = dfTitlesSample, x = 'imdb_votes', y =
'tmdb_popularity', cmin=0.5, cmap='viridis_r')
plt.colorbar()
plt.xlabel('imdb_votes')
plt.ylabel('tmdb_popularity');
```

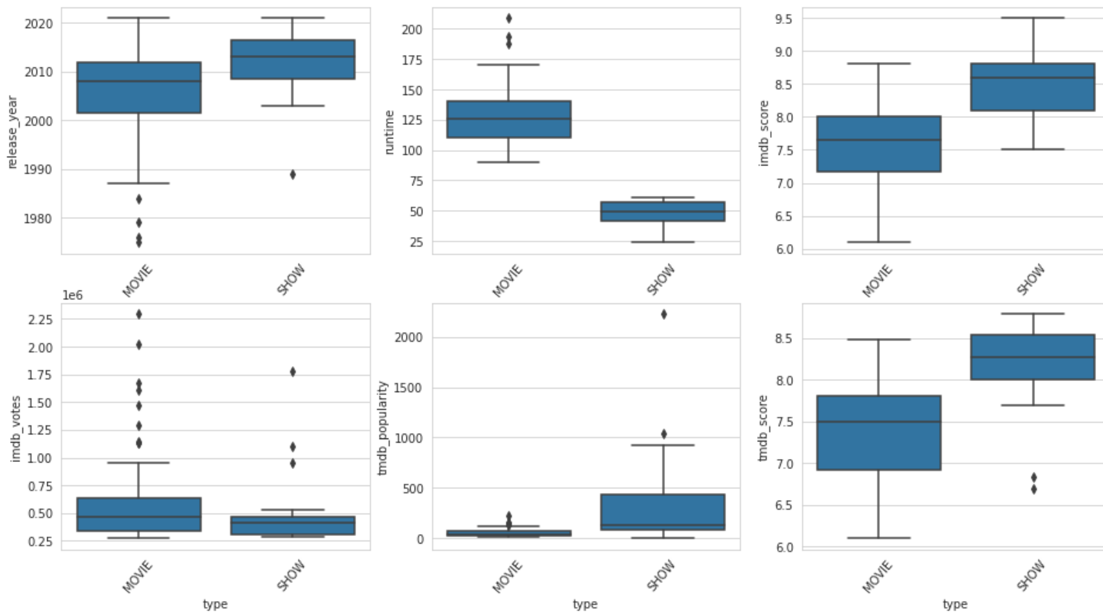



```
dfTitles.head()
```

```
    type  release_year  runtime                                    
genres  \
0   SHOW          1945       51                                    
['documentation']
1  MOVIE          1976      114                           ['drama', 
'crime']
2  MOVIE          1972      109  ['drama', 'action', 'thriller', 
'european']
3  MOVIE          1975       91              ['fantasy', 'action', 
'comedy']
4  MOVIE          1967      150                             ['war', 
'action']

  production_countries  imdb_score  imdb_votes  tmdb_popularity  
tmdb_score  \
0               ['US']    6.510861       23439            0.600  
6.829175
1               ['US']    8.200000      808582           40.965  
8.179000
2               ['US']    7.700000      107673           10.010  
7.300000
3               ['GB']    8.200000      534486           15.461  
7.811000
4         ['GB', 'US']    7.700000       72662           20.398  
7.600000

   cluster
0        0
1        2
2        3
3        1
4        3
```

```
# boxplot between type and some suitable variables
plt.figure(figsize = [16, 8.5])
```

```python
columsList = ['release_year', 'runtime', 'imdb_score', 'imdb_votes',
'tmdb_popularity', 'tmdb_score']

for i in range(len(columsList)):
    plt.subplot(2, len(columsList)//2, i+1)
    base_color = sns.color_palette()[0]
    sns.boxplot(data=dfTitlesSample, x='type', y=columsList[i],
color=base_color)
    plt.xticks(rotation=50);
```



Most of the data doesn't have many outliers which is good to work with this dataset.

4. CDA (Confirmatory Data Analysis)

4.1 Regression Models

4.1.1 Simple Linear Regression Functions

```python
# function that return a and b for simple linear regeression
def LR(x,y):
    # Mean X and Y
    mean_x = np.mean(x)
    mean_y = np.mean(y)
    # Total number of values
    n = len(x)
    # Using the formula to calculate 'a' and 'b'
    numerator = 0
    denomenator = 0
    for i in range(n):
        numerator += (x[i] - mean_x) * (y[i] - mean_y)
        denomenator += (x[i] - mean_x) ** 2
```

```
    a = numerator / denominator
    b = mean_y - (a * mean_x)
    return a,b

# function to call with x and y of the simple linear regerssion
def plotSLR(x, y):
    try:
        x = np.array(dfTitlesSample[x])
        y = np.array(dfTitlesSample[y])
        x_test = np.linspace(x.min(), x.max(),
num=len(dfTitlesSample))
    except:
        try:
            x = np.array(dfPricesSample[x])
            y = np.array(dfPricesSample[y])
            x_test = np.linspace(x.min(), x.max(),
num=len(dfPricesSample))
        except:
            print('there is no colums with these names')


    a,b = LR(x,y)
    print(a,b)
    y_pred = a*x_test + b
    plt.title("Simple linear regression")
    plt.plot(x_test,y_pred)
    plt.scatter(x,y);
```

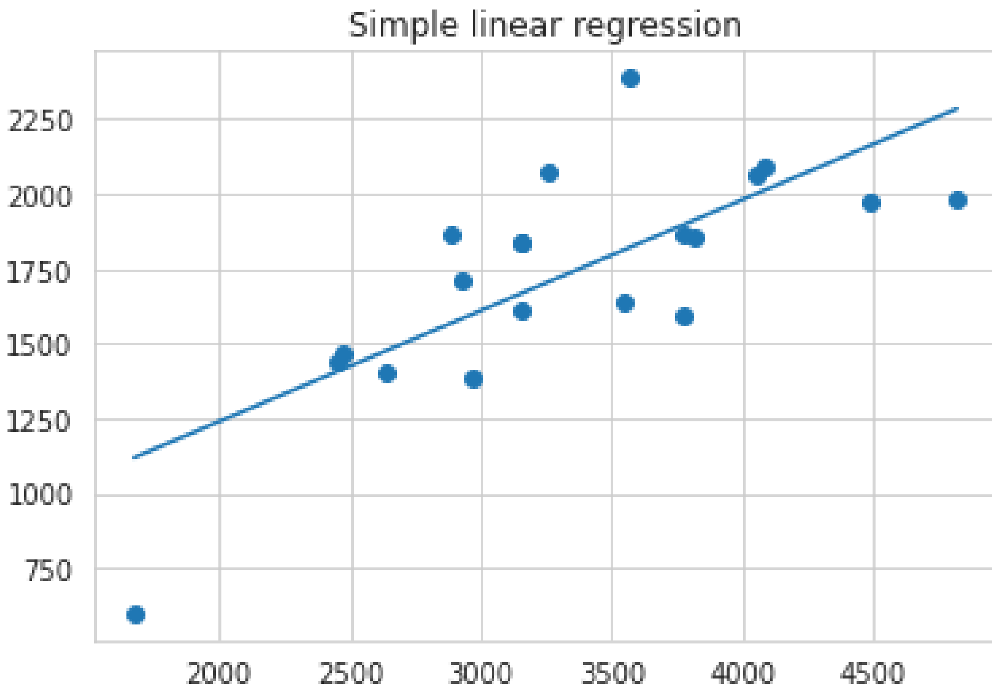
Prices data frame (First Simple Linear Regeression)

```
dfPrices_corr = dfPricesSample[['No. of TV Shows', 'No. of
Movies']].corr()
dfPrices_corr
```

	No. of TV Shows	No. of Movies
No. of TV Shows	1.000000	0.740333
No. of Movies	0.740333	1.000000

```
plotSLR('No. of TV Shows', 'No. of Movies')
```

```
0.3706171066614664 498.02199836533396
```



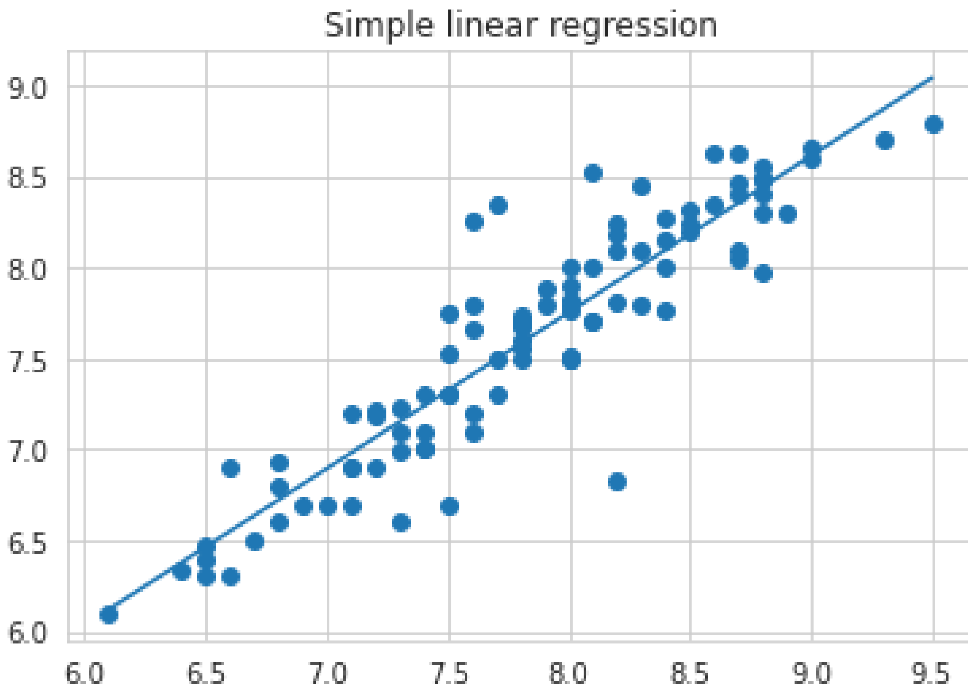
Titles data frame (First Simple Linear Regeression)

```
dfTitles_corr = dfTitles[['imdb_score', 'tmdb_score']].corr()
dfTitles_corr
```

	imdb_score	tmdb_score
imdb_score	1.000000	0.522002
tmdb_score	0.522002	1.000000

```
plotSLR('imdb_score', 'tmdb_score')
```

```
0.859118498078357 0.8802478009646597
```



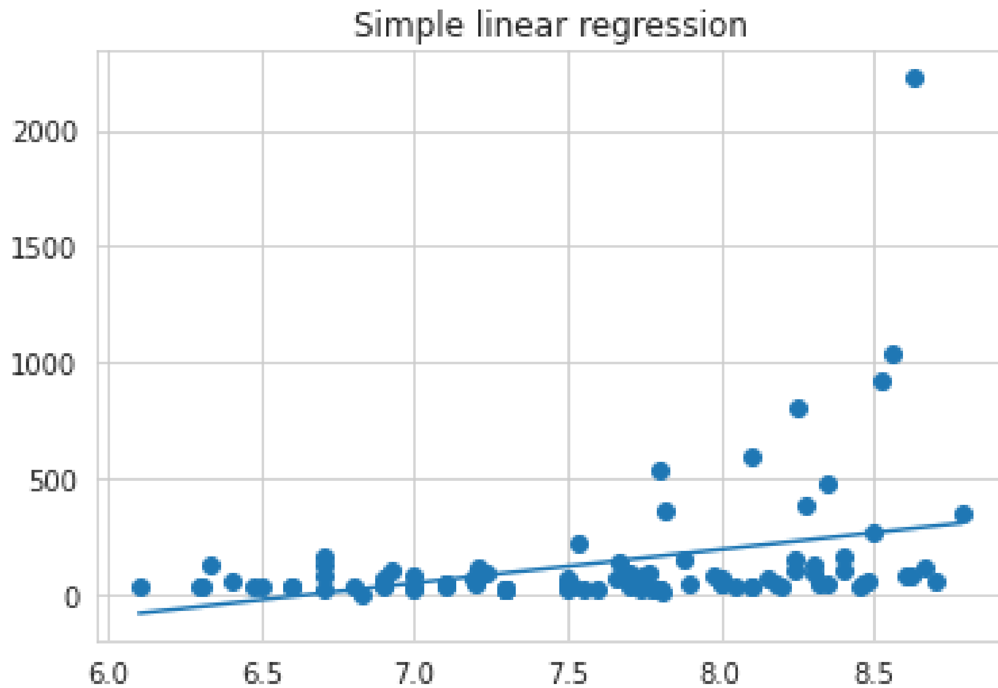
Titles data frame (Second Simple Linear Regeression)

```
dfTitles_corr = dfTitles[['tmdb_score', 'tmdb_popularity']].corr()
dfTitles_corr
```

	tmdb_score	tmdb_popularity
tmdb_score	1.000000	0.071793
tmdb_popularity	0.071793	1.000000

```
plotSLR('tmdb_score', 'tmdb_popularity')
```

144.72776892975168 -964.1765820875115



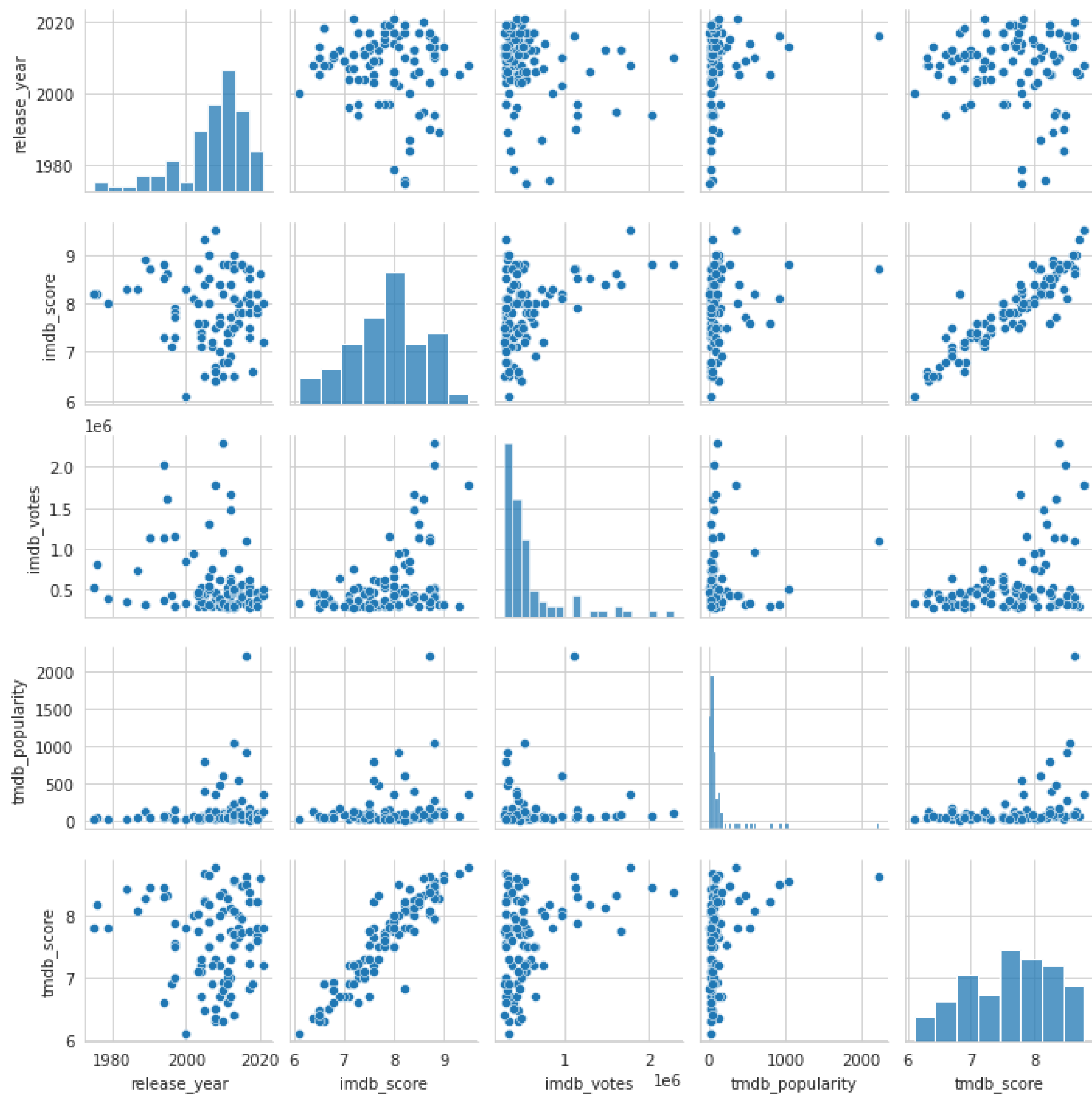
4.1.2 Multi Linear Regeression

```
dfTitlesSample

       type  release_year  runtime                                              
genres  \
1     MOVIE          1976      114                         ['drama', 
'crime']   
3     MOVIE          1975       91             ['fantasy', 'action', 
'comedy']   
6     MOVIE          1979       94                                              
['comedy']   
35     SHOW          1989       24                                              
['comedy']   
36    MOVIE          1990      145                         ['drama', 
'crime']   
...     ...           ...      ...                                              
...   
3061   SHOW          2020       56                         ['drama', 
'sport']   
3076  MOVIE          2019      209  ['crime', 'drama', 'history', 
'thriller']   
3095  MOVIE          2019      136             ['drama', 'romance', 
'comedy']   
4719   SHOW          2021       55             ['action', 'thriller', 
'drama']   
4726  MOVIE          2021      138               ['comedy', 'drama', 
'scifi']   
```

```
     production_countries  imdb_score  imdb_votes  tmdb_popularity  \
1                  ['US']         8.2      808582           40.965
3                  ['GB']         8.2      534486           15.461
6                  ['GB']         8.0      395024           17.770
35                 ['US']         8.9      308824          130.213
36                 ['US']         8.7     1131681           50.387
...                   ...         ...         ...              ...
3061               ['US']         8.6      420100           82.702
3076               ['US']         7.8      376379           21.075
3095               ['GB']         7.9      298303           28.268
4719               ['KR']         8.0      426967          361.925
4726               ['US']         7.2      515337          120.874

      tmdb_score  cluster
1          8.179        2
3          7.811        1
6          7.800        1
35         8.301        1
36         8.463        2
...          ...      ...
3061       8.624        1
3076       7.600        1
3095       7.800        1
4719       7.821        1
4726       7.208        1

[95 rows x 10 columns]
```

```
sns.pairplot(data = dfTitlesSample.drop(['cluster', 'runtime',
'genres'], axis=1), height = 2)
```

```
<seaborn.axisgrid.PairGrid at 0x7fa68d04b7c0>
```



```
dfTitles_corr = dfTitles[['release_year', 'imdb_votes',
'tmdb_popularity', 'tmdb_score']].corr()
dfTitles_corr
```

	release_year	imdb_votes	tmdb_popularity	tmdb_score
release_year	1.000000	-0.201884	0.043085	0.031140
imdb_votes	-0.201884	1.000000	0.206893	0.106151
tmdb_popularity	0.043085	0.206893	1.000000	0.071793
tmdb_score	0.031140	0.106151	0.071793	1.000000

Buliding The Multi Linear Regression Model

```
#Extracting Independent and dependent Variable
xColumns = ['release_year', 'imdb_votes', 'tmdb_score']

x = dfTitlesSample.loc[:, xColumns].values
y = dfTitlesSample.loc[:, 'imdb_score'].values
```

```
x = list(x)
y = list(y)

# Splitting the dataset into training and test set.
xTest = []
xTrain = []
for i in range(len(x)//4):
    randValue = random.randint(0, len(x))
    xTest.append(x.pop(randValue))
xTrain = x

yTest = []
yTrain = []
for i in range(len(y)//4):
    randValue = random.randint(0, len(y))
    yTest.append(y.pop(randValue))
yTrain = y

xtest = []
for i in xTrain:
    xtest.append(i[0])

#Fitting the MLR model to the training set:
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(xTrain, yTrain)

LinearRegression()

#Predicting the Test set result;
yPred = regressor.predict(xTest)
dfTitles1 = pd.DataFrame({'Real Values':yTest, 'Predicted
Values':yPred})
dfTitles1
```

	Real Values	Predicted Values
0	7.3	7.698550
1	7.7	8.156780
2	6.5	8.068978
3	8.8	8.029939
4	8.8	7.857304
5	8.9	7.479568
6	8.1	7.997191
7	7.5	7.382125
8	6.9	7.658690
9	8.1	7.676366
10	8.0	8.078286
11	7.2	8.164513
12	8.7	7.582988
13	8.7	7.866261

```
14          7.8          7.853938
15          7.4          7.764861
16          7.3          8.310314
17          6.8          8.075302
18          7.1          7.837653
19          7.4          8.231690
20          7.8          7.859611
21          9.3          8.189349
22          7.6          8.019149
```

```
regressor.predict([[2030, 40000, 7]])
```

```
array([7.50841946])
```

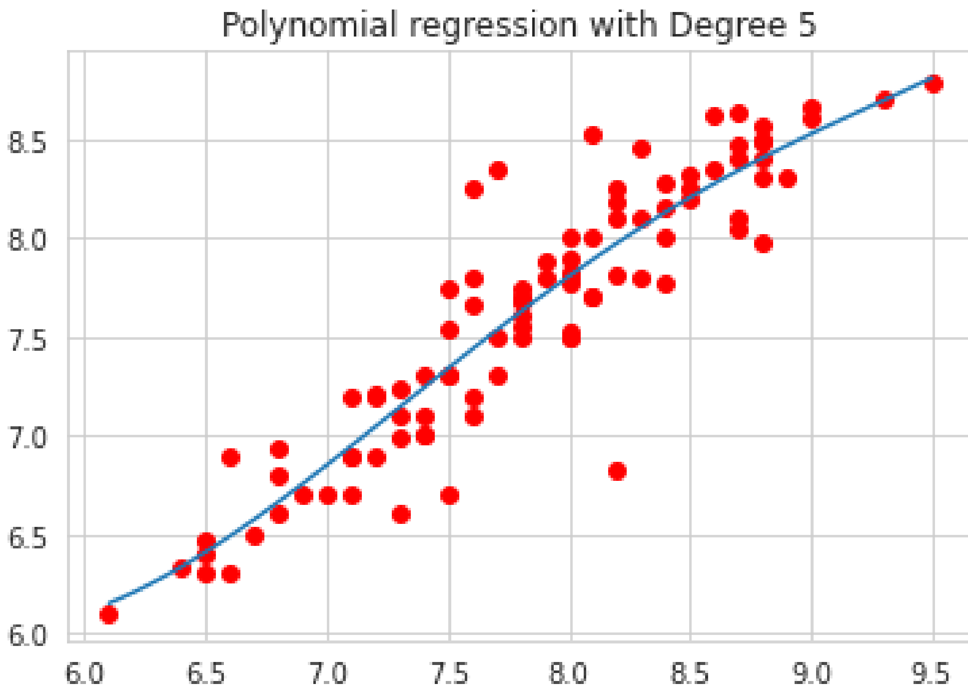
4.1.3 Polonomial Linear Regeression

```
dfTitles.head()
```

```
    type  release_year  runtime
genres  \
0   SHOW          1945       51
['documentation']
1  MOVIE          1976      114                          ['drama',
'crime']
2  MOVIE          1972      109  ['drama', 'action', 'thriller',
'european']
3  MOVIE          1975       91              ['fantasy', 'action',
'comedy']
4  MOVIE          1967      150                            ['war',
'action']

  production_countries  imdb_score  imdb_votes  tmdb_popularity
tmdb_score  \
0               ['US']    6.510861       23439            0.600
6.829175
1               ['US']    8.200000      808582           40.965
8.179000
2               ['US']    7.700000      107673           10.010
7.300000
3               ['GB']    8.200000      534486           15.461
7.811000
4         ['GB', 'US']    7.700000       72662           20.398
7.600000

   cluster
0        0
1        2
2        3
3        1
4        3
```

```python
x = np.array(dfTitlesSample['imdb_score'])
y = np.array(dfTitlesSample['tmdb_score'])
x_test = np.linspace(x.min(), x.max(), num=len(dfTitlesSample))

# Normal equation
def calculate_w(x,y):
    xt = x.T
    xt_x_inv = np.linalg.pinv(xt @ x)
    xt_y = xt.dot(y)
    w = xt_x_inv.dot(xt_y)
    return w

def polynomial(x, degree):
    x_pol = []
    for n in range(1,degree+1):
        x_pol.append(x**n)

    # array of ones represent the coefficent of bias
    x_pol.append(np.ones((len(x))))
    x_pol = np.array(x_pol).T
    return x_pol

degree = 5
x_pol = polynomial(x, degree) #[10, 3]
w = calculate_w(x_pol, y) #[4, 1]

x_test_pol = polynomial(x_test, degree)
print("Shape of x_test_pol", x_test_pol.shape)
print("Shape of W", w.shape)
y_pred = np.matmul(x_test_pol,w)


plt.plot(x_test, y_pred)
plt.title(f"Polynomial regression with Degree {degree}")
plt.scatter(x,y,c='r');
```

```
Shape of x_test_pol (95, 6)
Shape of W (6,)
```



Conclusion 1

We concluded that the mean values of the three categories of subscription are a little high and this means that netflix subscriptions may be unaffordable for some poor countries.

Conclusion 2

Netflix industry relies on TV Shows more than movies in the all the countries that are included in the sample.

Conclusion 3

Japanese Movies and TV Shows have the highest IMDB & TMDB score and this means that Japan has the high production quality.

Conclusion 4

The correlation between the cost of the three subscription plans is very high (positive correlation) and this means that if the client can afford the basic plan then he could afford the cost of the other two plans. However, this depends the client's needs.

Conclusion 5

High (positive) correlation between IMDB scrore and TMDB score, which means that good quality movies are really good because the score of the movie on both platforms is close to each other.

Conclusion 6

The predicted values are close to the real values which means that future predictions would be accurate. For example, we predicted the IMDB Score for a movie with a release year 2030 and IMDB Votes of 40,000 and TMDB Score of 7 and the results for the predicted IMDB Score was 7.63022984

Conclusion 7

For the polonomial regression we tried different polonomial degrees until we observed that the polonomial degree 5 is the best degree that fits the data more.